Can't Pay or Won't Pay? Unemployment, Negative Equity, and Strategic Default*

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Abstract

Prior research has found that job loss, as proxied for by regional unemployment rates, is a weak predictor of mortgage default. In contrast, using micro data from the PSID, this paper finds that job loss and adverse financial shocks are important determinants of mortgage default. Households with an unemployed head are approximately three times more likely to default compared to households with an employed head. Similarly, households that experience divorce, report large outstanding medical expenses, or have had any other severe income loss are much more likely to exercise their default option. While household-level employment and financial shocks are important drivers of mortgage default, our analysis shows that the vast majority of financially distressed households do not default. More than 80% of unemployed households with less than one month of mortgage payments in savings are current on their payments. We argue that this has important implications for theoretical models of mortgage default as well as loss mitigation policies. Finally, this paper provides some of the first direct evidence on the extent of strategic default. Wealth data suggest a limited scope for strategic

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default, with only $\frac{1}{3}$ of underwater defaulters having enough liquid assets to cover 1 month's mortgage payment.

1. Introduction

The impact of household-level financial shocks on mortgage default decisions has been debated for forty years.[1] Anecdotal and limited survey evidence suggest that life events such as job loss, illness and divorce play an important role, but no systematic evidence has been found due to the lack of information on household-level employment and income shocks in the loan-level datasets used by researchers to study mortgage performance. Many researchers have attempted to use aggregated unemployment and divorce rates as proxies for household-level shocks, but have found, at best, only weak correlations with default behavior.[2] In this paper, we use new mortgage default data from the Panel Study of Income Dynamics (PSID) to fill this gap in our understanding of the household mortgage default decision. The evidence we find largely confirms the anecdotes and survey findings.[3]

The first major finding of the paper is that household-level financial shocks play a major role in the default decision. In the sample as a whole, the default rate for households in which the head is unemployed is three times higher than for households in which the head is employed. Similarly, households that experience divorce, report large outstanding medical expenses, or have had any other severe income loss are much more likely to exercise their default option. Approximately 43% of households in default have suffered what we identify to be significant cash flow shocks (job loss, divorce, and/or severe income loss) in the year prior to default as opposed to only 16 percent in the population as a whole. Regression analysis confirms these basic patterns in the data. Controlling for the loan-to-value (LTV) ratio and a host of demographic, regional, and mortgage controls, we still find that unemployment

[1]Early empirical work on mortgage default includes Campbell and Dietrich [1983], Foster and Order [1985], Vandell [1995], Deng et al. [1996], Deng et al. [2000], Böheim and Taylor [2000], among others. Recent work on empirical mortgage default includes Foote et al. [2008], Haughwout et al. [2008], Mayer et al. [2009], Gathergood [2009], Goodman et al. [2010], Elul et al. [2010], Bhutta et al. [2011], and Mocetti and Viviano [2013] among others.

[2]See Gyourko and Tracy [2014] for a detailed discussion of how using aggregate unemployment rates as proxies for individual shocks could mask the true relationship between unemployment and mortgage default.

[3]See for example Hurd and Rohwedder [2010] who added questions to the RAND American Life Panel directly asking about whether or not households fell behind on their mortgage after losing their job (about 8.6% of the 699 households surveyed said they fell behind).

and other cash flow shocks have economically and statistically significant effects on the probability of default. We estimate that job loss by the head of household has an impact on default rates that is equivalent to a 45% reduction in home equity. Likewise, job loss by the spouse is equivalent to a 31% reduction in equity.

The data clearly show that unemployment and individual household finances have a large influence on a household's decision to default. But the data allow us to query further and to determine *how* they matter. We start with the standard taxonomy of default popular in the literature in which defaulters are divided into two groups. The first are "can't pay" defaulters, who are unable to afford their mortgage payments because of job loss or some other life event. The second group are "won't pay" defaulters, also known as strategic defaulters in the literature. "Won't pay" households can afford the mortgage payment but treat the mortgaged property as a call option to repurchase the home for the outstanding balance on the mortgage, as in Kau and Keenan [1995]. Using standard option pricing techniques, the "won't pay" households default if the value of the call option falls short of the mortgage payment.

The data provide some support for the existence of "can't pay" defaulters. More than 40% of all defaulters are either unemployed, have recently gotten divorced or have exceptionally high medical expenses. Furthermore, approximately two-thirds of households in default have liquid asset holdings that amount to less than one monthly mortgage payment and 84% have holdings of less than two mortgage payments. In contrast, the data suggest the existence of a much smaller group of "won't pay" or strategic defaulters. We show below that the median defaulter can only make $\frac{1}{3}$ of one monthly mortgage payment with their liquid assets. Additionally, only 10% of households in default have four months or more of mortgage payments in the bank and about 5% have more than 5 months. In general we find that households in default have very low levels of wealth.

While the evidence on "can't pay" and "won't pay" defaulters is consistent with prior survey findings, the data also present a striking puzzle for the "can't pay"/"won't pay" dichotomy. Suppose we define "can't pay" to be households without a job and with less than one month of mortgage payments in stock, bonds, or liquid assets (net of unsecured debt). The data show that approximately 19 percent of these "can't pay households" are in default as compared to only 4 percent in the population as a whole. What is surprising though is the flip side of that 19 percent: 81 percent of "can't pay" households are *current* on their loans. In other words, despite no income and no savings, most households in this group continue to pay their mortgages. Furthermore, we show that these striking patterns remain even when conditioning on negative equity. The "double trigger" model of mortgage default that has received a good deal of attention in the literature posits that it is the combination of household-hold level shocks and negative equity that drives the majority of mortgage defaults. While we do find a higher default rate among "can't pay" borrowers with negative equity (33 percent), it is still the case that the majority of these borrowers are current on their mortgage payments (67 percent).

On the flip side we find that less than 1 percent of "can pay" households, which we define to be households that are employed and have at least 6 months worth of mortgage payments in stock, bonds, or liquid assets (net of unsecured debt) are in default. Conditioning on negative equity does not have much effect as only 5 percent of "can pay" borrowers with negative equity are in default. Thus, the vast majority of borrowers in positions of negative equity continue paying their mortgages, which suggests that strategic default rarely occurs.

The existence of so many "can't pay" but "do pay" or "non-strategic non-defaulters" in the data requires some explanation. The first important insight is that while "can't pay" may seem like a logical concept in principle, it is problematic in the data because income and liquid assets are not the only potential sources of funds for borrowers. Among other things, borrowers can tap unsecured debt markets. The PSID does not provide information on credit limits but the Survey of Consumer Finances (SCF) does and it shows that homeowners in default have available credit equal to 3.6× their monthly mortgage payment, on average.[4] In

[4]The average homeowner in default in the SCF has unused credit (credit limit less outstanding balances) equal to 3.6× their monthly mortgage payment whereas the median household has unused credit equal to

other words, borrowers may be taking out unsecured loans to pay their mortgages. Another possibility is that they are borrowing or receiving assistance from relatives or from other sources.[5]

But just knowing that they can take out unsecured debt to make mortgage payments does not explain why so many households choose to continue making payments when the consumption cost of doing so is so high. One possibility is that the economic cost of default is high. The appearance of a foreclosure in an individual's credit history severely impacts their ability to access debt markets. In addition it also affects job prospects which are, ironically, particularly important to jobless workers. Furthermore, there are non-economic costs that play an important role; survey evidence shows that many people believe that defaulting on a mortgage is an immoral act.[6]

Our findings have important implications for theoretical models of mortgage default. The fact that household-level financial shocks are important determinants of default behavior implies that frictionless, option-theoretic models of mortgage default (for example, Kau and Keenan [1995] and Vandell [1995]) are at significant odds with the data. Furthermore, the fact that so many households who default *can* pay or, more specifically, that observably identical households in the data *do* pay, suggests that the popular double-trigger model of mortgage default is also at significant odds with the data. We argue that there is an alternative class of existing models with some potential in being able to rationalize these findings. Specifically, the models developed in Corbae and Quintin [2009], Garriga and Schlagenhauf [2009], Chatterjee and Eyigungor [2011], Campbell and Cocco [2011], and Laufer [2012], which include important features like borrowing constraints and heterogeneous agents that allows for interactions between income, savings, and home equity in the decision to default, can, in principal, match the empirical stylized facts found in this paper. However, our results suggest that these models need substantial distortions that damper the appeal

0.4× their monthly mortgage payment.

[5]Disaggregated borrowing data from the 2011 PSID suggests relatively few defaulters borrow from relatives, see Appendix G.

[6]See Wilkinson-Ryan [2011] and Bridgeman [2011] as well as citations therein.

of default in order to match the extremely high fraction of financially distressed borrowers that do not default in the data.

Our findings also have significant implications for policy. In particular, we argue that the finding of low default rates among "can't pay" borrowers, could significantly complicate loss mitigation policies. We show that the size of a payment or principal reduction that a lender is willing to offer to a financially distressed borrower is increasing in the probability of that borrower defaulting. Thus, low probabilities of default among distressed borrowers reduce the ability of the lender to mitigate foreclosures.

The remainder of the paper is structured as follows. Section 2 describes the PSID data and discusses the representativeness of the sample. Section 3 summarizes the types of shocks that characterize defaulters and describes the baseline results. Section 4 measures the incidence, income, and wealth of "can't pay" and "won't pay" households and, in doing so, provides several direct measures of strategic default. Section 5.1 describes the relation of our findings to existing models of mortgage default and discusses the implications of our results for loss mitigation policies. Finally, Section 6 concludes.

2. PSID Data

The primary data used in this study come from the 2009 and 2011 PSID Supplements on Housing, Mortgage Distress, and Wealth Data. We restrict the sample to mortgagor heads who report being in the labor force and who are between the ages of 24 and 65. We also restrict our sample to households with LTV ratios less than 250% who had not defaulted in a prior survey.[7] This leaves us with 5,281 households.

In the remainder of this section we discuss the representativeness of the PSID data regarding housing and mortgage market variables and then present a detailed set of summary statistics for the sample of all households and the sample of households in default.

[7] The LTV requirement drops what appear to be misreported mortgage and home values (inclusion of these observations does not change our main results), and dropping defaulting households from future observations simply eliminates double counting.

2.1. Representativeness of PSID Sample

Table 1 compares mortgage statistics between our PSID sample with the 2011 National American Housing Survey (AHS).[8] In general, mortgage characteristics are quite similar across the two datasets. Median outstanding principal balance is identical and the median monthly mortgage payment is within $100. The median mortgage interest rates, remaining terms, and LTV ratios are also extremely close across the datasets. A slightly higher fraction of mortgagors report having a second mortgage (18% versus 13%) and an adjustable-rate mortgage (9% versus 7%) in the PSID.

The Delinquency rates among mortgagors in the PSID are slightly lower than other nationally representative datasets. According to the National Delinquency Survey conducted by the Mortgage Bankers Association (MBA), the average 60+ day delinquency rate in 2009 was 5.8%, whereas in the PSID it was approximately 4%.[9] Similarly, the 30+ day delinquency rate in 2009 according to the MBA was 9.4% compared to 6.5% in our PSID sample.[10]

Finally, Figure 1 displays the distribution of housing equity in our sample compared to Corelogic.[11] According to Corelogic, slightly more than 10% of properties had greater than 25% negative equity, while slightly less than 4% do so in the PSID. While there could be many reasons for the divergence in equity estimates between the two databases, households

[8]The AHS is conducted biennially by the U.S. Census Bureau. It has a sample size of about 47,000 housing units and was designed to provide representative data on the U.S. housing and mortgage markets.

[9]Throughout the paper, we do not weight the observations due to the fact that default outcomes are not post-stratum in the PSID. The point is best made with an important example. As mentioned in the text, the MBA reports an average 60+ day delinquency rate in 2009 of 5.8%. In the 2009 PSID, the unweighted default rate among mortgagors is 3.86%. However, the default rate in the 2009 PSID, weighted using the family weights, is only 3.15%. The weights significantly lower the default rate compared to the unweighted default rate and yield a default rate roughly half the magnitude of the population default rate. A similar set of outcomes is also true in the SCF. The additional set of results with and without the weights is simply to demonstrate that the main asset distribution results are insensitive to the weights.

[10] The Board of Governors of the Federal Reserve System also publishes delinquency rates among FDIC insured banks, and they report an average 30+ day delinquency rate of 9.1% averaged over 2009.

[11]The bottom panel of Figure 1 comes from the August 13, 2009 report entitled "Summary of Second Quarter 2009 Negative Equity Data from First American CoreLogic" `http://www.loanperformance.com/infocenter/library/FACL%20Negative%20Equity_final_081309.pdf` Corelogic uses a national database of property transactions that covers 43 states to come up with their equity estimates, and thus should be quite representative of the U.S. population. Corelogic uses administrative data on outstanding mortgage balances and estimates of housing values to compute equity, while we use reported mortgage balances and housing values in the PSID.

tend to over-report house values as compared to actual selling prices by 5% to 10% (see Benítez-Silva et al. [2008]). While the PSID understates the amount of negative equity in the economy relative to Corelogic estimates, we do not view this as a significant drawback of our analysis. To determine the dual roles that negative equity and unemployment have in causing mortgage delinquency and default, we believe that self-reported equity is the most appropriate equity measure. In choosing whether or not to default, households take into account their own perceived valuation of their home, which may or may not be derived in part from a third party estimate (such as Corelogic or Zillow). To put it another way, the value of using self-reported equity values is that only those households who believe that they are in positions of negative equity are given negative equity, and this is the group of households whom we expect to be most sensitive to negative equity in terms of their default behavior.[12]

2.2. PSID Summary Statistics: All Households

In this section we focus on summary statistics for all households in our PSID sample. Below, in section 2.3, we present a similar set of summary statistics for only the households who are delinquent on their mortgage payments.

Panel A of Table 2 displays demographic information. The average age of the household heads in our sample is approximately 44 years. About 85% of the household heads in our sample are male, 74% are white and 21% are black. The majority of households in the sample are married (74%) and have heads with at least some college education (about 60%). Average household income is approximately $110 thousand, while median income is $87 thousand.

Panel B of Table 2 displays mortgage information. Households were asked how many months they were behind on their mortgage payments at the time of the PSID interview.

[12] In addition it is likely the case that many households have information about the condition of their home and the state of their local housing market that is not captured in data-based estimates such as the Corelogic numbers, which use zip-code-level or county-level house price indices to estimate property values.

Approximately 5.95% of mortgagors (N = 314) were 30+ days late on their mortgage payment, whereas 3.6% of mortgagors (N = 190) were at least 60 days late on their mortgage payment. In the remainder of the paper we will adopt the definition of default that corresponds to two or more payments behind (i.e. at least 60+ days delinquent), as this is the convention in the literature. The average and median LTV ratio in the sample is 71%. LTV ratios are calculated as the sum of total liens on a residence (1st, 2nd, and 3rd) to self-reported home value. On average, households have about 21 years remaining on their respective mortgages and owe $150 thousand. The average monthly mortgage payment is $1,253, the average interest rate paid on first mortgages is just over 5%, and only 9% of first liens in the sample have adjustable rates. Almost 20% of households in the sample also have an outstanding second mortgage.

Panel C of Table 2 contains employment information. In our sample 6% of household heads report being unemployed as of the survey date, while 8% report being unemployed as of the survey date or at some point during the year prior to the survey. Approximately 10% of households report that either the head or spouse was unemployed at the time of the survey, and 13% report that either the head or spouse was unemployed at some point during the prior year.

Panel D of Table 2 displays information on the non-housing wealth of households at the time of the survey. Households hold $20 thousand in liquid assets and $127 thousand in illiquid assets on average,[13] and report, on average, approximately $16 thousand in unsecured debt.[14] The wealth distribution is highly skewed in the sample as the median household holds only $5 thousand in liquid assets and $12 thousand in illiquid assets (all from vehicles).

[13]Liquid assets are defined as the sum of all checking or savings accounts, money market funds, certificates of deposit, government savings bonds, and Treasury bills. Illiquid assets are defined as the sum of equity and bond holdings, the value of automobiles, retirement accounts, and business income. These variables are measured only once, as of the survey date.

[14]Unsecured debt is defined as credit card charges, student loans, medical or legal bills, and loans from relatives. Hospital bills includes outstanding debt owed to a hospital or nursing home.

2.3. PSID Summary Statistics: Defaulters

The questions asked in the PSID regarding mortgage delinquency, employment, and the household balance sheet allow us to uniquely characterize defaulters in a degree of detail that is new to the literature. In Table 2 we show summary statistics pertaining to the sample of households that are delinquent on their mortgages. Most notably, heads of household in default have an unemployment rate of 21% as compared to 6% for all mortgagors. If we consider unemployment among spouses, 31% of households in default have an unemployed spouse or head versus 13% for non-defaulters. Households in default are also significantly different along many demographic margins. For example, only 17% of defaulters attained a college degree versus 33% of all mortgagors, and 55% of households that default are married compared to 74% of all mortgagors. Furthermore, defaulters are relatively low-income households with income more than $40,000 less than the average mortgagor.

In terms of mortgage characteristics, the median household in default has an LTV ratio of 94%, while the average LTV ratio among defaulters is 101%. A much higher fraction of households in default have adjustable-rate mortgages (22% versus 9% of all mortgagors). Households in default pay a higher monthly mortgage payment and are faced with a higher interest rate on average. The average household in default is approximately 5 months behind on mortgage payments, while the median household in default is 3 months behind.

Panel D in Table 2 shows that households in default have significantly lower liquid and illiquid assets compared to the sample of all mortgagors. Households in default have approximately $17 thousand less in liquid assets and $92 thousand less in illiquid assets than the average mortgagor. In addition, households in default have slightly more unsecured debt on average ($18 thousand versus $16 thousand)

The resounding message from this comparison is that households in default are far from the average mortgagor along almost every measurable dimension, particularly in terms of employment and wealth, which are unobservable quantities in most mortgage-level data sets.

3. Default and Household-level Financial Shocks

In this section we identify the relationship between household-level financial shocks and mortgage default. We use the full set of information on household income, wealth, employment status, marital status, and health status in the PSID to construct measures of adverse, household-level, financial shocks that could be important in generating variation in mortgage default behavior. We pay particular attention to employment shocks as unemployment spells have been the focus in much of the previous literature.

We begin by constructing an unemployment shock, which we define as a household head who reports being unemployed at the time of the survey or reports a positive duration unemployment spell over the 12 months prior to the survey date. We also construct a spousal unemployment shock using the same definition. We define a 'low liquid asset' shock to be a household that has insufficient liquid assets to cover one month's mortgage payment (23.8% of the sample falls into this category). We define a 'high unsecured debt' shock to be a household that has unsecured debt greater than 5 years' worth of mortgage payments (5.1% of the sample falls into this category). A 'high medical bills' shock is defined as annual medical bills greater than one year's worth of mortgage payments (21.3% of our sample falls into this category), while a 'high hospital bills' shock is defined as annual hospital bills greater than one year's worth of mortgage payments (1.1% of the sample falls into this category). We define a divorce shock as a household head who reports having gone through a divorce since the previous survey (15.8% of the sample falls into this category).

We also define several composite shocks such as 'cash flow' shocks (recent divorce, unemployment of head or spouse, or a 50% reduction of income) as well as generic 'any non-equity' shocks (recent divorce, unemployment of head or spouse, a 50% reduction of income, low liquid assets, high hospital bills, or high medical bills). Approximately 17% of the sample suffered a cash flow shock, and 57.4% of the sample suffered a generic non-equity shock.

3.1. Unconditional Default Rates by Shock Status

Table 3 describes both the default rates among households who suffered various shocks (Panel A), as well as the fraction of defaulters and non-defaulters who suffered each type of shock (Panel B). We see that the default rate associated with unemployed households (10.1%) is roughly triple that of employed households (3.0%). The same is true for households with and without negative equity, which we define here as an LTV ratio above 100%. The largest difference in default rates is between households with and without low liquid assets.

Moving to Panel B of Table 3, we see that 23.2% of heads of households that defaulted were unemployed, 42.1% of defaulters had negative equity, 43.2% of households that defaulted had a cash flow shock, and nearly 86.3% of defaulters had a generic non-equity shock. Nearly two thirds of households in default (66.8%) did not have enough liquid assets to meet a single monthly mortgage payment. These percentages are all significantly lower for households that did not default. Furthermore, approximately 6% of households in default were recently divorced compared to only 2% of non-defaulting households. In contrast, the difference in the incidence of the high hospital bill shock between the two types of households is much smaller (2.1% versus 1%).

Taken as a whole, the results reported in Table 3 imply that household-level employment and financial shocks are important determinants of mortgage default. Below we show that this remains true when we condition on a host of borrower and loan characteristics.

3.2. Regression Results

In the previous section we presented an analysis of unconditional default rates that was highly suggestive of the importance of household-level financial shocks in the default decision. In this section we conduct a multivariate analysis, in which we control for numerous observable household and mortgage characteristics in an attempt to determine whether there is a causal relationship between these financial shocks and household default behavior. We present estimates from linear probability models (LPMs) as well as logit models.

Columns (1) and (2) in Table 4 illustrate the basic relationship between the unemployment shock and the probability of mortgage default using a LPM. The dependent variable in each regressions is a dummy variable corresponding to whether or not the household is in default. Column (1) does not include controls for demographics, mortgage characteristics, or geographic (state-level) differences, while column (2) includes controls.[15] The addition of controls approximately doubles the R^2 of the regression, and has a non-trivial impact on the coefficient estimates associated with the unemployment shock, although it does not have a significant impact on the LTV ratio coefficient estimate. According to column (2), households with an unemployed head are about 5 percentage points more likely to default compared to households with an employed head, and households with both an unemployed head and spouse are about 9 percentage points more likely to default than an employed household. This is a huge effect considering the fact that the default rate across all households in our sample is only 4%. Equity is also highly correlated with default. According to column (2), an increase in the LTV ratio of 20% is associated with a 1.9 percentage point increase in the likelihood of default (0.2*0.094). To make things a bit more comparable we can use the estimates in column (2) to determine the loss of equity that would cause the same increase in the propensity to default as an unemployment shock. According to the estimates, an unemployment shock to the household head is equivalent to an increase in the LTV ratio of roughly 56% (0.053/0.094), while an unemployment shock to the spouse is equivalent to a 43% (0.04/0.094) increase in the LTV ratio.

In column (3) of Table 4 we add additional financial shocks to the model to see whether other types of shocks are predictive of mortgage default. The inclusion of the additional shocks slightly decreases the estimated coefficients on the LTV and unemployment shock

[15]The control set includes a complete set of race dummies, a gender dummy, a marriage dummy, dummies for educational levels, dummies for whether the state allows lender recourse and judicial foreclosure, and an indicator for whether the household lives in AZ, CA, FL, or NV, the states that experienced the largest house price declines and worst foreclosure problems. In addition we add variables that measure state-level house price growth in the year prior to the survey and the change in the state-level unemployment rate over the same period. We also include controls for mortgage characteristics, which include the type of mortgage (ARM vs. FRM), the interest rate, the remaining term, the presence of a second mortgage, and whether or not the mortgage is a refinance of a previous loan.

variables. The only shock that is statistically significant is the low liquid assets shock, which has an estimated effect on default that is similar in magnitude to the unemployment shock. The interpretation of the low liquid assets shock is unclear however, as it may be the case that financially distressed households run down their assets before choosing to default. If so, then the correct interpretation would be that households are experiencing other forms of financial distress and running down their assets as opposed to suffering a direct shock to their assets that causes them to default. While the coefficient estimates associated with the other types of financial shocks are not statistically significant, the point estimates associated with the high hospital bills shock and the recently divorced shock are relatively large.

In column (4) we add an interaction term between the LTV ratio and the unemployment shock. The interaction is positive and statistically significant, reflecting the fact that for greater levels of negative equity, the impact of job loss on the likelihood to default is larger. An unemployment shock at a LTV ratio of 80% is associated with a 5.8 percentage point (0.8*0.1-0.022) increase in the propensity to default, whereas an unemployment shock at a LTV ratio of 1.2 is associated with a 9.8% (1.2*0.1-0.022) increase in the propensity to default.

Finally, columns (5) and (6) of Table 4 substitute state-level unemployment rates for the individual measures. As we discussed in the introduction, previous studies were had to use aggregate unemployment rates, often at the state-level, to proxy for unemployment shocks. Many of those studies found an extremely weak relationship between aggregate unemployment rates and default, which we also find. State-level unemployment rates by themselves and state-level rates interacted with LTV ratios are not correlated with default in our PSID sample. This confirms the claim by Gyourko and Tracy [2014] that using aggregate unemployment rates as a proxy for individual unemployment shocks results in a serious attenuation bias.

Table 5 displays estimation results using a logit model rather than a LPM. We report both average marginal effects (AMEs) in columns (1) and (2) and marginal effects at the mean (MEMs) in columns (3) and (4). In general, the results are similar to those obtained in the LPM. We see that in Column (2), the estimated increase in the likelihood of default if the household becomes unemployed is 6.3 percentage points, on average. Likewise, the average increase in default rates from a 20% increase in LTV ratios is 1.36 percentage points (0.2*0.068). It is notable however, that the interaction between LTV ratios and unemployment is statistically insignificant in column (2). Turning to column (3), if we hold the covariates at their mean, unemployed households are 5.4 percentage points more likely to default, on average, than employed households, ceteris paribus. Likewise, if the LTV ratio increases by 20% the default rate is estimated to increase by 1.04 percentage points (0.2*0.052). In the online appendix, we explore the non-linearity of this relationship in more detail.

3.2.1. Robustness: Involuntary Job Loss

A potential criticism of the baseline results reported above is that the unemployment shock may be endogenous to the household rather than an entirely exogenous event. Some unemployment spells are voluntary and initiated by the employee, and it is possible that the estimated relationship between unemployment and default is driven by households who are defaulting due to some other event, which also happens to be characterized by voluntary job separation. To address this issue, columns (1) and (2) of Table 6 isolate job losses due to involuntary separations, which are defined in the PSID to be either a plant closure, strike/lockout, or layoff. The results are quantitatively similar to the benchmark results in Table 4. The point estimates remain essentially unchanged, with involuntary job loss being equivalent to a 54% decline in home equity. However, since there are only 220 instances of involuntary separation in our sample, the standard errors are slightly larger and the interaction term in Column (2) is insignificant (the interaction term confounds the impact of involuntary job loss itself).

3.2.2. Robustness: Unobserved heterogeneity

A similar potential criticism of the baseline results is that they may be driven by unobserved heterogeneity across households rather than reflecting a causal relationship from unemployment shocks to mortgage default. For example, perhaps some households are bad types and are just more likely to be laid off and more likely to default. Impatient households who heavily discount the future might be more likely to default on debt and may also be more likely to be fired due to poor work habits. If this unobserved factor does not vary over time, then the panel dimension of the PSID allows us to address the issue. To do so we construct indicator variables based on the number of prior unemployment spells over the seven PSID surveys spanning 1994-2005, and include these variables in our control set.

Columns (3) and (4) of Table 6 display estimation results from a linear probability model that includes the prior unemployment shock indicator variables. The coefficient estimates associated with the LTV ratio variable and all of the financial shocks including the current unemployment shock dummy are largely unaffected. Unemployment is still equivalent to a 55% percent reduction in home equity.

3.2.3. Robustness: House Price Expectations

Another important factor in the household mortgage default decision, which is unaccounted for in the regressions discussed above and could confound the estimation results is households' expectations of future house price movements. While the PSID does not contain direct measurements of house price expectations, we propose two indirect methods for controlling for expectations. The first is to assume that households have rational expectations, which implies that they do not make systematic errors in their forecasts. Operating under this assumption, we take self-reported house price growth from 2009-2011 for each of the households in the 2009 survey, and use it as a control variable. Columns (5) and (6) in Table 6 display the results. The inclusion of future self-reported house price appreciation does not affect the coefficient estimates associated with the unemployment variables or other financial shock variables.

Our second method for controlling for house price expectations is to assume that agents have adaptive expectations, and form their forecasts based solely on previous housing price dynamics. Based on this assumption, we control for lagged self-reported house price growth. Lagged self-reported house price growth is measured from 2007 to 2009 for households in the 2009 survey and from 2009 to 2011 for households in the 2011 survey. Columns (7) and (8) of Table 6 report the main set of results including lagged house price growth as a control. We find that the inclusion of lagged house price growth does not impact the results.

3.2.4. Robustness: Survey of Consumer Finances

In Appendix B, we use the 2007-2009 Survey of Consumer Finances (SCF) panel dataset to double check our PSID results. Similar to the PSID, the SCF collected default information in the 2009 wave of interviews. However, the confounding factor in the SCF is the timing and precision of the questions. The main problems include, (i) the default question in the SCF refers to default over the last 12 months and is not confined to simply secured debt (let alone mortgages), (ii) there is no separate category for health expenses (the closest is medical loans which are included with "other" loans), (iii) there is no data on consecutive unemployment spells, and lastly, and (iv) since the default status at the survey date is unknown and since they record negative equity, wealth, and employment as of the survey date, causal inference is nearly impossible. We use nearly identical sample restrictions as the PSID, limiting ourselves to mortgagors; however, it remains ambiguous as to whether the default occurred on the mortgage or an unsecured line of credit. With these caveats in mind, we find similar results in the SCF. Becoming unemployed is equivalent to a 49% reduction in equity. In specifications where we allow for an interaction between unemployment and equity, we find that unemployment nearly doubles triples the impact of any given equity loss on default propensity. Appendix B includes a more thorough explanation of these results.

3.2.5. Robustness: Generic Cash Flow and Non-Equity Shocks

Table 7 illustrates the impact of cash flow shocks, generic non-equity shocks, and income loss on the propensity to default. Columns (1) and (2) show that the presence of a cash-flow shock (unemployment of head or spouse, divorce, or 50% income loss) is equivalent to a 55% reduction in equity. In column (2) we allow for the cash flow shock to interact with the loan-to-value ratio. We find a significant interaction between the cash-flow shock and LTV. The effect of an equity reduction is nearly 2x larger in the presence of a cash-flow shock. Columns (3) and (4) allow for generic 'any non-equity' shocks. In general, we find very similar results to the cash-flow shock. Columns (5) and (6) include a dummy for a 50% income decline. Once again the magnitude of the results are quite similar with an income decline being equivalent to a 71% decline in equity. The interaction term in column (6) between equity and severe income loss is insignificant, likely due to the small incidence of such large drops in income.

4. Do too many borrowers default or too few? Double trigger and strategic default

Our analysis above found strong evidence that unemployment and household-level financial shocks play an important role in a household's decision to default on its mortgage. This is important as it confirms the suspicions of many researchers and market participants who have long believed that employment status and financial health are important determinants of a household's decision to default. In this section, we focus on a simple model of default known as double trigger and discuss its implications, particularly with respect to what is known as strategic default.

As background, there are two standard ways that researchers have thought about mortgage default. The first is to treat the house as a financial asset and use asset pricing techniques from finance (which we discuss in more detail in the next section). The second is a heuristic commonly referred to as the "double trigger" model.[16] The two triggers in "double trigger" are negative equity and an individual household shock. The idea is that negative equity is a necessary condition for default as the household will never default with positive equity because it can sell the house. The sufficient condition is that the household suffers a "life event," which results in the inability to continue making mortgage payments. Double trigger is not an optimizing model, but, as we will argue below, it underpins a lot of important thinking about the subject.

How does double trigger stack up against the data? At first blush, the answer appears to be reasonably well. In the analysis above we found that both equity levels and household-level employment and income-related shocks are important predictors of mortgage default. In addition, we found some evidence that the combination of the two factors further increased the probability of default (Table 4 and Table 6), so that households with the combination of negative equity and a "life event" appear to be much more likely to default than those who face either negative equity or a "life event" but not both. Thus, it is tempting to conclude that the simple double trigger model is a reasonable approximation to the data.

However, further analysis generates a more nuanced and striking view of the data. The starting point here is that, according to double trigger, if we focus on borrowers with negative equity, inability to pay is necessary and sufficient for default. If we divide up negative equity borrowers into those that "can pay" who have sufficient financial resources, either in terms of flow of income or stock of assets, to pay their mortgage and those that "can't pay," who do not, default should only occur for the can't pay borrowers. Figure 3 illustrates this by dividing negative equity borrowers up by whether they can or cannot pay and whether they did or did not pay. According to double trigger, only the diagonal elements of the figure should be populated. As far as double trigger is concerned, we can view the off-diagonal elements as errors. Type I error, the upper right corner, corresponds to borrowers who the model predicts will pay but don't and Type II error, the lower left corner, corresponds to

[16]See Section 5.1 for a discussion of both types of models.

borrowers who the model predicts won't pay but who continue to pay.

What we call Type I error here, people who can pay but don't, has generated considerable attention both among academics and policy makers who refer to them as "strategic defaulters." Researchers, including Guiso et al. [2010], Bhutta et al. [2011], Keys et al. [2012], have focused on identifying borrowers who appear to be able to pay but choose instead to default. Type II error, borrowers who can't pay but do, has, on the other hand, received comparatively very little attention.

The challenge in bringing double trigger to the data is the phrase, "can't pay." To an economist, "can't pay" means that the mortgage payment is outside of the household's budget set. In other words, even if the household sold all of its worldly possessions, starved, and borrowed the maximum possible amount from available creditors it would not be able to make the payment. But in common usage, and for the heuristic of double trigger, it is more appropriate to think that a borrower can't pay if paying involves an unreasonable sacrifice. A borrower can pay, on the other hand, if paying involves what we would think of as a reasonable sacrifice.

In the remainder of this section we attempt to identify "can't pay" and "can pay" households in our data and then using those definitions, we assess the importance of strategic defaulters (Type 1 error) and borrowers that continue to pay despite appearing to not have the financial means to do so (Type II error). Overall, we find the evidence on whether the data support the double-trigger theory of mortgage default to be mixed. While Type I error is extremely small in our data, Type II error is widespread.

4.1. Identifying "Can Pay" and "Can't Pay" Households

In taking the idea of "can pay" and "can't pay" borrowers to the data, we confront two issues. The first is that, as mentioned above, whether a borrower "can pay" or "can't pay" a mortgage is a matter of opinion and any definition is somewhat arbitrary. As a result, we come up with very strict definitions of "can pay" and "can't pay" that we think most reasonable people would agree with. The second problem is timing. Ideally, we would like to have all relevant information as of the same moment in time. For example, to assess whether the borrower can pay *this month* we would like to know whether the borrower is delinquent *this month* and how much income the borrower has *this month*. However, in the PSID, information on income is only provided for the calendar year prior to the survey year whereas wealth and employment information are reported as of the survey date. For example, we will know if a particular household had no income last year but we have no information on whether it was delinquent on its mortgage payments last year. Alternatively, we know if the household is delinquent and whether it is employed or unemployed at the survey date, but we do not how much income it has at that time. With these two issues in mind, our baseline definitions are:

(1) **Can Pay:** Head of household is employed as of the survey date and the household has at least 6 months worth of mortgage payments in stock, bonds, or liquid assets net of unsecured debt.

(2) **Can't Pay:** Head of household is unemployed as of the survey date and the household has less than 1 month's worth of mortgage payments in stock, bonds, or liquid assets net of unsecured debt.

Table 8 displays a detailed set of summary statistics for each category. The first thing to note is that because our definitions are quite strict, the "can pay" and "can't pay" categories are not even close to exhaustive. The two categories combined account for slightly less than half of our PSID sample. Panel (A) describes the demographics and income of each subset of households. The "can pay" households have median annual gross family income of $110k, almost twice as large as the "can't pay" households, which have a median annual gross family income of about $58k. The "can pay" households are significantly more likely to be college educated and have on average fewer children. In addition the "can't pay" group is made up of a much higher fraction of minority households, and is more likely to include single households and households headed by a woman.

If we focus on the subsets of can and can't pay borrowers that default, we find that, regardless of whether they can or can't pay, defaulters are more likely to be minority households, are more likely to be single households, and are more likely to be headed by a female compared to their non-defaulting counterparts. In addition they both have less income, on average than their non-defaulting counterparts. However, in comparison to each other, there are some striking differences. "Can pay" households that default have more than twice as much income on average, are much better educated, are more likely to be headed by a male, and are significantly more likely to be black compared to "can't pay" households that default.

Panel (B) of Table 8 displays basic mortgage characteristics. On average, we see in the panel that "can pay" households' hold significantly larger loans compared to "can't pay" households. "Can pay" households, on average, have significantly lower LTV ratios, lower mortgage coupons, are more likely to have a fixed rate mortgage, and are more likely to have a refinanced loan. Defaulters, for both can and can't pay subsets, are much more likely to have ARMs than non-defaulters. Panel (B) shows that the can pay borrowers who default have a mean LTV of 1.25 and a median of closer to 1. In contrast, the mean and median LTV ratios associated with the can't pay borrowers are below 1.

Panel (C) of Table 8 describes the employment status of the head and spouse for each category. Since employment of the head is used to define the groups, it is largely degenerate. Only 2% of "can pay" households had a head that was unemployed at some point last year and subsequently employed as of the survey date (recall this is a condition to be in the "can pay" group). Spouses in the "can't pay" households as well as those in the "can pay" category who default are much more likely to be unemployed as of the survey date.

Panel (D) of Table 8 describes the wealth of each category. On average, the "can pay" subgroup has significant holdings of stocks, bonds, and liquid assets. On the other hand, by construction, the "can't pay" subgroup has virtually no assets, with median liquid asset holdings of only $500. The "can pay" subset of households that default have lower liquid assets than their non-defaulting counterparts, but compared to the "can't pay" subgroup, these households have significantly more of every category of asset.

4.2. Default Behavior of Can and Can't Pay borrowers

The first row of Table 9 shows that only about 1% of "can pay" households actually default compared to 19% of "can't pay" households. Of course this implies that 99% of "can pay" households are not in default, while more than 80% of "can't pay" households continue making their mortgage payments. The double trigger model implies that we should further restrict our attention to borrowers with negative equity. The second row of Table 9 shows that if we focus on borrowers with negative equity, the share of "can pay" borrowers who default rises to 5% and for "can't pay" borrowers it rises to 33%.[17] Returning to our language from above, we see that Type I error is quite small. Of the borrowers that the double trigger model predicts should pay, approximately 95% actually do pay. In contrast, Type II error is huge. According to double trigger, can't pay borrowers should default but the data shows that about 2/3 of them continue to pay. We now discuss Type I and Type II error in turn.

4.2.1. Type II error: Why do so few unemployed households with no savings default?

One possibility for why we find so few defaults among can't pay households is that our definition isn't strict enough. In Rows (3) to (6) of Table 9, we show default rates using a definition of can't pay in which *both* the head and spouse are out of work, and the household has less than 1 month's worth of mortgage payments in stock, bonds, or liquid assets net of unsecured debt. We find that the share of defaults conditional on having negative equity actually goes down slightly from 33 percent to 30 percent. In other words, approximately

[17]Table 9 also shows that these results hold true even if we lower the cutoff for negative equity to a combined loan-to-value ratio of 0.9.

70% of households in negative equity positions, in which both the head and spouse are unemployed, and in which household liquid assets are less than one month's mortgage payment are current on their mortgages.

To understand the "can't pay" households better, we estimate the effect of equity on default for only the subsample of "can't pay" households. A priori, we would expect that if these households are truly unable to afford making their mortgage payments, then equity should not play any role whatsoever in that decision, and thus, we should not find a correlation across "can't pay" households between equity and the propensity to default. Table 10 reports estimates of linear probability models in which a default indicator is regressed on LTV ratios along with the same demographic controls and state controls that were used in the baseline regressions presented in section 3. The first two columns of Table 10 display regression results for the "can pay" households, while the last two columns display results for the "can't pay" households. Unsurprisingly we see that the decision to default for the "can pay" households is negatively correlated with the amount of equity in their properties. All relevant theories of mortgage default predict that equity should be one of the primary determinants of optimal mortgage default for unconstrained borrowers. The results for the "can't pay" households are fairly striking though. While the precision of the LTV coefficient estimates is low due to the small sample size of the "can't pay" group, the point estimates are more than twice as large as those for the "can pay" group of households. Thus, it appears that the default decision for "can't pay" households may be even *more* sensitive to equity levels relative to the decision for "can pay" households.

One obvious concern about the estimated magnitude of Type II error here is the small PSID sample. Is it reasonable to extrapolate these numbers to the broader population of underwater mortgage borrowers? To address this issue, we compare them with aggregate data. In 2009, the Bureau of Labor Statistics (BLS) reported that there were about 15 million unemployed workers and the Mortgage Bankers Association (MBA) reported that there were about 2.7 million loans that were more than 60 days past due. This implies that in 2009, unemployed workers outnumbered past due households by a ratio of about 5:1. This 5:1 ratio is about the same as the ratio of all can't pay homeowners to delinquent can't pay homeowners in our PSID data. While these ratios are in no way dispositive, the point is that the aggregate data also displays a similar low number of defaults relative to distressed households.

It is also worth noting that the PSID data, while not perfect, is better, in many cases, than the data available to market participants. Unlike borrowers applying for loans, who have an incentive to overstate their income, or delinquent borrowers applying for relief from their lender, who have an incentive to understate their income, PSID participants have no incentive to lie about their employment status or income. We return to this topic when we discuss policy implications later in the paper.

On the face of it, it seems hard to believe that borrowers with no job and little to no savings could and would continue to pay their mortgages. However, the PSID does not contain information on households' access to credit. Credit could come in the form of unsecured debt from lenders or it could come less formally from family members or friends. To shed light on these issues, we turn to two additional data sources. In the 2011 PSID, we have disaggregated data on loans from family members. We find that loans from family members are rare, and only about 10% of the can't pay defaulters and less than 10% of the overall defaulter population in the PSID received assistance in this form (see Appendix G). To address the issue of access to more formal credit markets, we turn to the SCF.[18] In the SCF, we find that defaulters have less than one half of one month's mortgage payment available in unused credit. Because of several outliers, the average unused credit for a defaulter is approximately 3 month's of mortgage payments. While this evidence is not conclusive, it does suggest relatively limited roles for family lending and unsecured borrowing among defaulters.

[18]In the SCF, as mentioned above, the default data suffers from severe time aggregation bias. In addition, the type of defaulted debt is not specified.

4.2.2. Type I Error: Evidence of Strategic Default

As already mentioned, our measure of Type I error is known in the popular press and among many academics as "strategic default." While there is no consensus in the literature on an exact definition of strategic default, the term is often interpreted to describe a borrower in a position of negative equity who has plenty of financial resources to continue to make mortgage payments, but instead chooses to default. For example, Mian and Sufi [2009] define instances of strategic default as "defaults where a borrower has the cash flow to make mortgage payments, but chooses to default nonetheless because of negative equity in the house." Similarly, Guiso et al. [2010] define the concept as "households' propensity to default when the value of their mortgage exceeds the value of their house even if they can afford to pay their mortgage."

Our data suggests that strategic default is rare. We find that less than 1% of "can pay" households default on their mortgages. If we focus our attention on "can pay" households with negative equity, this percentage does rise, but only slightly, to about 5 percent. We now use the detailed data on wealth in the PSID to elaborate on the extent of strategic default in the data. Table 11 presents information on the wealth distribution of households that default with negative equity. The table displays information on the liquid asset distribution, the illiquid asset distribution, the distribution of the sum of liquid and illiquid assets net of unsecured credit owed, which we refer to as net non-housing wealth, and the distribution of the sum of liquid assets and stocks and bonds. We normalize everything by the monthly mortgage payment and show both unweighted (Panel A) and weighted (Panel B) summary statistics. There are a few notable patterns in this table. First, the vast majority of households that default with negative equity have very low levels of liquid assets. The median household in default with negative equity can only make approximately $\frac{1}{3}$ (unweighted) to $\frac{2}{3}$ (weighted) of one monthly mortgage payment with its liquid assets, while 75% of these households do not have enough liquid assets to make two payments, and 90% report having liquid asset levels that are less than four mortgage payments.

While very few negative equity defaulters have high levels of liquid assets, there is a non-trivial fraction that have relatively high levels of illiquid assets. According to the table, 25% of these households hold more than 16 months' worth of mortgage payments in illiquid assets, while 10% hold more than 30 months' worth. These numbers drop a bit when we net out unsecured debt levels. Should we interpret these statistics as evidence that many households are strategically defaulting? Before jumping to any conclusions, it's important to remember that illiquid assets are, by their nature, costly to access. Recall that we define illiquid assets in this paper to include equity and bond holdings, the value of automobiles, retirement accounts, and business income. It may be relatively easy to liquidate equity and bond positions, but withdrawing from a retirement account and selling a car can be very costly propositions, especially if owning a car is necessary to remain employed. In the last row of each panel we report the distribution of liquid assets combined with stock and bond holdings, which we believe are likely the easiest of the illiquid assets to access. This distribution looks very similar to the distribution of liquid assets only. For example, 75% of negative equity households have less than 2 months' worth of mortgage payments in liquid assets plus stock and bond holdings.

For comparison purposes, Table 12 displays the same statistics for non-defaulting households. The differences in the distributions are striking. The median household that is not in default holds approximately 5 months' worth of mortgage payments in liquid assets, and more than 20 months' worth of payments in illiquid assets. The non-defaulting households hold significantly higher levels of wealth compared to the negative equity defaulters. Our takeaway from Tables 11 and 12 is that there is minimal evidence of strategic default in the data as the vast majority of negative equity defaulters have very little wealth. To the extent that there are some negative equity defaulters that do have non-trivial levels of wealth, most of that wealth appears to be in forms that are highly illiquid. Thus, our interpretation of the data is that strategic default and Type I error are quite small in reality.

5. Implications for Research and Policy

In this section, we first discuss the implications of our analysis for the study of household mortgage default decisions. We then show that these findings illustrate the challenges of assisting distressed borrowers in a housing crisis.

5.1. Modeling default

Our starting point here is the double trigger model discussed in the previous section. Double trigger has the advantage that it is simple and it gets some key features of the data right. First, double trigger predicts that job loss and other household level shocks increase the likelihood of default. While that may seem obvious, another workhorse model which we discuss below, predicts that individual household shocks should have no effect on the probability of default. The second success of the double trigger model is that it predicts that borrowers who can pay their mortgages will pay their mortgages and, as we showed in the last section, that is not a bad approximation to the data. Specifically, we showed that approximately 99 percent of borrowers with ample income and considerable savings made their mortgage payments and that conditioning on negative equity only resulted in that share decreasing to 95 percent. However, the double trigger model fails along two key dimensions. The first is that double trigger implies that the effect of equity on default is binary. In particular, it predicts that any strictly positive level of equity is sufficient to prevent default. But Figure 2 shows that regardless of whether they are employed or not, borrower behavior is sensitive to the precise level of equity. Less equity implies more default even at very high levels of negative equity. The second problem is that the double trigger model predicts that all "can't pay" borrowers should default and, as we documented in the previous section, most do not.

An alternative to double trigger is the "frictionless option model" (FOM) which has been the standard theoretical treatment of the topic since Asay [1979] who was the first to apply the option pricing model of Black and Scholes [1973] to mortgages (see also Kau et al. [1993]

and Kau and Keenan [1995]). The FOM assumes that households have access to unlimited opportunities to borrow and save at the riskless rate and can hedge both the house price and interest rate risk associated with the mortgage. The main result of the FOM is that one can treat the combination of the house and the mortgage as a call option. The borrower sells the house to the lender and gets a call option to buy the house back from the lender by paying a strike price equal to the outstanding balance on the mortgage. If the value of the call exceeds the monthly payment on the mortgage then the borrower makes the payment; if the value of the call falls short, and the borrower cannot sell the house for more than the outstanding balance, then the borrower defaults. The key insight of the model is that the value of the call depends only on the interest rate and house price processes and not on the borrower's individual situation. Borrower income, borrower assets, borrower employment, and even borrower beliefs about house prices do not matter in the model.

The FOM succeeds in one key respect. In the double trigger model, the threshold level of LTV for default is 100, whereas in the FOM the threshold LTV almost always exceeds 100. To understand why, recall that the basic intuition is that the mortgage is a call option. Negative equity simply means that the call option is out of the money but the great insight of option theory is that an out-of-the-money option is typically worth more than zero so with a sufficiently low mortgage payment, it always makes sense to continue paying. For any two identical mortgages on identical houses, the FOM predicts a unique threshold LTV, but in the data we would expect to see a distribution of threshold LTV levels and a continuous relationship between LTV and default which is what we see in Figure 2 for both "can pay" and "can't pay" borrowers.

The FOM fails along two dimensions. First, the prediction of the FOM that borrower employment does not affect default is at odds with the data. Our findings show that conditional on a level of negative equity, unemployed borrowers are 3 times more likely to default than employed borrowers whereas, according to the FOM, individual employment status should have no predictive power at all.

The second failure of the FOM has to do with the "can pay" borrowers. Unlike the double trigger model, the FOM predicts that some "can pay" borrowers will default, and in fact, under reasonable parameterizations, the model predicts that *a lot* of "can pay" borrowers will default. For example, Kau et al. [1993], in their baseline example, calculate that 100 percent of borrowers with LTVs above 115% will default. That prediction is difficult to reconcile with our finding that among can pay borrowers, only 5% of borrowers with negative equity default on their payments. In addition, Panels A and C of Figure 2 show that default rates in our data never exceed 25%, even for the subsample of households with LTVs above 150% who have not suffered a liquidity shock.

To improve on the FOM, researchers have built dynamic models of households who maximize lifetime utility, consume both goods and housing services, and finance the purchase of homes with mortgages on which they can default.[19] The key innovation is that these models include an array of realistic frictions including borrowing constraints, risks that cannot be fully hedged, moving costs and, typically, default penalties that often include losing access to mortgage markets for a specified period of time. As a result, we will refer to these models as *frictional models*. It is important to stress that the basic logic that a mortgage is a call option still applies here. In a sense, the FOM is just a special case of these models with all of the constraints stripped away.

In discussing frictional models, it is useful to separate out the effects of borrowing constraints because they are different from the effects of other frictions. If we consider a model in which households have stochastic labor income and face borrowing constraints, the similarities and differences with the FOM are easy to explain. Recall that in the FOM, the borrower trades off the cost of making the mortgage payment with the benefit of the payoff of the call option on the house at some future date. If a household faces a binding borrowing constraint, then, all else equal, the marginal utility of current consumption is higher. As a result, the cost of the mortgage payment rises relative to the payoff on the call option and

[19] Examples include Corbae and Quintin [2009], Garriga and Schlagenhauf [2009], Chatterjee and Eyigungor [2011], Campbell and Cocco [2011], Schelkle [2011], and Laufer [2012].

default becomes more attractive.

Introducing borrowing constraints produces a model that is more realistic than both the FOM and double trigger models along two key dimensions. On one hand, it improves on the FOM because borrowing constraints mean that shocks to a household's financial condition now matter. Thus, the model can, like double trigger and unlike the FOM, rationalize the strong effects of employment and financial shocks that we see in the data. On the other hand, even in the presence of borrowing constraints, the basic intuition of the FOM that the LTV default threshold does not equal 100 still holds. In other words, we would still expect there to be a continuous relationship in the data between LTV and the probability of default.

There is one problem, however, that borrowing constraints cannot solve, which is that the number of defaults predicted by the model will still vastly exceed what we observe in the data. For the households not facing borrowing constraints, the predictions in Kau et al. [1993] still imply that all borrowers will default if LTV exceeds 115. But, for households suffering shocks, the threshold LTV will be even lower which, again, is completely at odds with what we see in the data.

The frictional models recognize that borrowing constraints alone cannot make the model realistic and so they introduce the additional frictions mentioned above. The key point about these other frictions – moving costs, the inability to obtain another mortgage, and others – is that they make default much *less* attractive. As a result, some of these frictional models can generate the low default rates that we observe in the data.

However, the problem with introducing these frictions is that they are something of a black box. Laufer [2012], for example, structurally estimates the implied rent-to-price ratio that defaulters face in the rental market, writing that:

> The rent-price ratio that prevails in the post-default rental market is $\rho = .17$, which equals 0.68 in annual terms. This estimate captures not just the true cost of rental housing but all the costs associated with default including the distaste

> for renting, the impact on the homeowners credit score and any potential stigma. This value is approximately ten times the true rent-price ratio, indicating a high cost of default.

In other words, the parameter ρ captures a list of things that researchers cannot measure and Laufer's estimate of the parameter implies that they must be very large.

In addition, there is reason to believe that these frictions may differ enormously across households. In other words, dispersion in costs could explain why some "can't pay" borrowers stick it out while others do not.

There are other potential explanations for these patterns that have been offered in the literature, which involve variables that we do not observe in the PSID. A priori, access to either unsecured credit markets or to the wealth of relatives/friends could play an important role. However, as we discussed in Section 4.2.1, there is relatively little evidence of loans from relatives in the 2011 PSID (which specifically tracks these types of loans), and the SCF reveals that the median defaulting household has relatively little unused credit available. Unsecured borrowing is usually very expensive, e.g. the Flow of Funds reports interest bearing credit accounts were assessed nominal interest rates of between 12.95% and 14.68% during the Great Recession. While much family assistance may be "off-the-books," it's not clear whether either unsecured credit or family assistance alone could explain the fact that 80% of the "can't pay" households in our sample continue making payments. However, there may be other unobservable factors at play, which combined with other unobserved credit markets, could explain these low default rates.

One possibility along these lines is that many households have a strong moral aversion to defaulting on debt, especially mortgage debt. For example, Guiso et al. [2010] find evidence in survey data that many households consider strategic mortgage default to be an immoral practice, and as a result, are much less likely to engage in such behavior.[20] Approximately 82% of the households in their survey report having a moral aversion to mortgage default, so

[20] The definition of strategic default used by the authors is a scenario in which a borrower can afford to make the mortgage payment, but chooses not to.

it is conceivable that a large majority of our "can't pay" households hold similar reservations against default.

Another possibility is that many households have a strong attachment to their homes, and thus go to extreme measures to avoid default and foreclosure. Finally, optimistic expectations of future house prices may play an important role. The theoretical literature tells us that house price expectations are an important determinant in the decision to default. While it's hard to believe that optimistic expectations alone could explain why 80% of households with no income or assets continue making payments, such an explanation is at least consistent with the evidence on the sensitivity of default decisions to equity displayed in Table 10.

5.2. The problem of loss mitigation

When a lender forecloses on a loan, the losses are typically quite substantial. For starters the collateral is typically worth less than the outstanding balance on the loan. In addition, the foreclosure process takes a long time during which the lender receives no income from the loan and incurs substantial administrative costs. Many argued during the financial crisis in 2008 that the losses on foreclosures were so large that lenders could save money by renegotiating the mortgage and giving borrowers payment or principal reductions that both avoided the foreclosure and saved money for investors. To see this formally, we follow Foote et al. [2008] and consider a lender with a borrower who owes m dollars on a house currently worth p_h dollars who will default with probability α_0, in which case the lender recovers p_h less λ dollars in foreclosure costs. A modification lowers the value of the loan to $m^* < m$ and the probability of foreclosure to $\alpha_1 < \alpha_0$. Some simple arithmetic shows that the modification is both profitable for investors and prevents foreclosure if:

$$\underbrace{(\alpha_0 - \alpha_1)}_{\substack{\text{Reduction in} \\ \text{foreclosure prob.}}} \times \underbrace{(m^* - (p_H - \lambda))}_{\substack{\text{Reduced} \\ \text{loss}}} > \underbrace{(1 - \alpha_0)}_{\substack{\text{Pct. repay without} \\ \text{mitigation}}} \times \underbrace{(m - m^*)}_{\substack{\text{Reduced value of} \\ \text{the mortgage}}} . \quad (1)$$

The left hand side measures the gain to investors resulting from foreclosure prevention: for measure $\alpha_0 - \alpha_1$, investors recover $m^* > p_H - \lambda$. The right hand side, however, measures a cost that is often ignored in discussions of renegotiation. For the measure $1 - \alpha_0$ set of borrowers who would have repaid their loans in full either way, the lender now recovers $m* < m$.

To understand why our findings above are relevant to renegotiation, suppose that the double-trigger model is an accurate description of borrower behavior. In that case, if we observe borrowers who have negative equity and are suffering from adverse income/financial shocks, we will know that all of those borrowers will default on their respective mortgages. In other words, α_0 would equal 1 meaning that the right hand side of equation (1) would equal zero. As a result, the lender could, in principle, prevent *all* foreclosures and increase profits.

The challenge for renegotiating loans generated by our findings regarding the extent of Type II error is that α_0 is significantly smaller than 1. To illustrate the point, suppose that we take an estimate of $\alpha_0 = 1/3$, which is at the high end of the default rate that we estimated for "can't pay" borrowers with negative equity and we assume that $\alpha_1 = 0$, meaning that renegotiation prevents all foreclosures (i.e. re-default rates are zero). Then, for renegotiation to be profitable the following condition must hold:

$$\frac{m^* - (p_H - \lambda)}{m - m^*} > \frac{(1 - \alpha_0)}{(\alpha_0 - \alpha_1)} = \frac{2/3}{1/3} = 2 \tag{2}$$

which implies that:

$$m - m^* < (1/3) \cdot (m - (p_H - \lambda)) \tag{3}$$

In other words, the maximum profitable reduction in debt is 1/3 of the difference between what the borrower owes and the recovery value from foreclosure. To see the problem, consider a borrower with an LTV of 150% and assume that the lender can recover only 75% of the value of the house through foreclosure (the average foreclosure recovery rate is 78% as reported by Pennington-Cross [2006]). Equation (3) implies that the maximum possible modification would only lower the balance to an LTV of 125%.

To make matters worse, our data involves a sample of borrowers who have no incentive to lie about their income and employment. For lenders, the challenge of equation (1) is compounded by the fact that borrowers have every incentive to understate their income and employment. In other words, our figure of a 1/3 probability of default for borrowers who report no income and employment may well be high relative to what we would obtain if we used what borrowers report to their lenders rather than to the PSID interviewers. Indeed, for HAMP, the government's signature foreclosure prevention program, documentation of income was the most significant obstacle to facilitating renegotiation.[21]

6. Conclusion

In order for policymakers to respond to the 2007-2009 foreclosure crisis, it is necessary to understand the sources of mortgage default. While there is broad agreement that a number of factors may potentially contribute to default, including equity, employment, and liquidity, due to data limitations (particularly in terms of the employment status of the household), it has been impossible to directly test the relative importance, as well as interactions, among such factors. In this paper we make three contributions to the literature. First, we use new household level data to quantitatively assess the roles that (i) job loss, (ii) negative equity, and (iii) other financial shocks play in default decisions. In sharp contrast to prior studies that proxy for individual unemployment status using regional unemployment rates, we find that unemployment is one of the most important determinants of default. Job loss by the head of household is equivalent to a 45% reduction in home equity. Second, we show that while household level employment and financial shocks are important drivers of mortgage default, the vast majority of distressed households do not default on their

[21] See, "The mod squads; Treasury unleashes loan-relief 'SWAT teams.' Will it help?" *Washington Post*, 2 December 2009.

respective mortgages. This finding has important implications for theoretical models of mortgage default and the optimal design of loss mitigation policies. Finally, we provide evidence on the importance of strategic default in the data. We find only a minimal role for strategic default as most households that default have very low wealth levels, and most households in positions of negative equity with relatively high wealth choose not to default.

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Table 1: PSID vs. American Housing Survey

	PSID (2009-2011)	AHS (2011)
	Medians	
Principal Remaining ($)	120,000	120,000
Monthly Mortgage Payment ($)	1,100	1,015
Mortgage Interest Rate	5.0	5.3
Mortgage Term Remaining (Years)	24	22
LTV Ratio	0.71	0.71
	Fraction with	
Second Mortgage	0.18	0.13
ARM	0.09	0.07

Notes: AHS 2011 National Statistics taken from Table C-14A-OO. PSID Sample: Heads of household who are mortgagors, ages 24-65, labor force participants with combined loan to value ratios less than 250% in 2009 and 2011. Defaulting households are dropped after default to avoid double counting.

Table 2: Summary Statistics for All PSID Households Heads in Sample, 2009-2011

(A) Demographics

	All Households				Delinquent Households			
	Mean	p10	p50	p90	mean	p10	p50	p90
Age	44.08	30	44	58	43.19	31	42.5	57
Male (d)	0.85	0	1	1	0.68	0	1	1
Married (d)	0.74	0	1	1	0.55	0	1	1
Less than High School (d)	0.08	0	0	0	0.14	0	0	1
High School Education (d)	0.26	0	0	1	0.33	0	0	1
Some College Education (d)	0.27	0	0	1	0.29	0	0	1
College Grad+ Education (d)	0.33	0	0	1	0.17	0	0	1
Number of Children	1.01	0.0	1.0	3.0	1.23	0.00	1.00	3.00
Income	110,000	38,000	87,000	180,000	64,000	21,000	55,000	120,000

(B) Mortgage Characteristics

	All Households				Delinquent Households			
	Mean	p10	p50	p90	mean	p10	p50	p90
Home value	240,000	80,000	180,000	450,000	190,000	50,000	140,000	350,000
Principal Remaining	150,000	35,000	120,000	290,000	180,000	31,000	130,000	350,000
Monthly Mortgage Payment	1253	500	1100	2200	1349	459	1100	2528
Second Mortgage (d)	0.18	0	0	1	0.21	0	0	1
Refinanced Mortgage (d)	0.46	0	0	1	0.40	0	0	1
ARM (d)	0.09	0	0	0	0.22	0	0	1
Mortgage Interest Rate	5.15	4	5	7	5.81	0	6	9
Mortgage Term Remaining	20.56	7	24	29	23.10	10	25	30
Recourse (d)	0.24	0	0	1	0.26	0	0	1
Judicial (d)	0.39	0	0	1	0.38	0	0	1
Default (60+ Days Late) (d)	0.04	0	0	0				
Months Delinquent	0.20	0	0	0	4.95	2	3	11.5
Loan to Value Ratio	0.71	0.28	0.71	1.04	1.01	0.52	0.94	1.66

(C) Employment

	All Households				Delinquent Households			
	Mean	p10	p50	p90	mean	p10	p50	p90
Unemployed Head Last Year (d)	0.08	0	0	0	0.23	0	0	1
Unemployed Spouse Last Year (d)	0.05	0	0	0	0.12	0	0	1
Unemployed Head or Spouse Last Year (d)	0.13	0	0	1	0.31	0	0	1
Head Unemployed as of Survey Date (d)	0.06	0	0	0	0.21	0	0	1
Spouse Unemployed as of Survey Date (d)	0.04	0	0	0	0.10	0	0	1
Unemployment Duration	0.26	0	0	0	0.97	0	0	3
Unemployment Duration, Spouse	0.20	0	0	0	0.52	0	0	0

(D) Wealth

	All Households				Delinquent Households			
	Mean	p10	p50	p90	mean	p10	p50	p90
Value of Stocks	21,000	0	0	25,000	2,655	0	0	0
Value of Liquid Assets	20,000	0	5,000	45,000	3,238	0	250	5,000
Unsecured Debt	16,000	0	4,354	40,000	18,000	0	6,750	40,000
Value of Vehicles	19,000	2,000	12,000	40,000	11,000	0	8,000	27,000
Value of Bonds	13,000	0	0	6,800	14,000	0	0	0
Business Income	41,000	0	0	0	4,973	0	0	0
Value of IRA	33,000	0	0	90,000	1,870	0	0	0
Value of Other Housing	29,000	0	0	30,000	3,794	0	0	0
N	5281				N	190		

Notes: Default defined as 60+ days late as of survey date. PSID Sample includes heads of household who are mortgagors, ages 24-65, labor force participants with combined loan to value ratios less than 250% in 2009 and 2011. Defaulting households are dropped after default to avoid double counting. Pooled averages and pooled distributions reported above. Liquid assets include checking and savings account balances, money market funds, certificates of deposit, Treasury securities, and other government saving bonds.

Table 3: Summary of Shocks and Default Rates

	Panel A: Default Rates Among Subgroups of Households							
	Unemployed?		Negative Equity?		Low Liquid Assets?		Income Drop of 50% or More?	
	Yes	No	Yes	No	Yes	No	Yes	No
Default Rate	10.1%	3.0%	11.3%	2.4%	10.1%	1.6%	10.7%	3.3%
# of HHs in Subgroup	435	4846	708	4573	1256	4025	233	5048
	Recently Divorced?		Cash Flow Shock?		Any Non-Equity Shock?		High Hospital Bills?	
	Yes	No	Yes	No	Yes	No	Yes	No
Default Rate	9.7%	3.5%	8.9%	2.5%	5.4%	1.2%	7.0%	3.6%
# of HHs in Subgroup	113	5168	919	4362	3031	2250	57	5224

	Panel B: Among Defaulters/Non-Defaulters, How Many Had Shocks?							
	Unemployed?		Negative Equity?		Low Liquid Assets?		Income Drop of 50% or More?	
	Defaulters	Non-Defaulters	Defaulters	Non-Defaulters	Defaulters	Non-Defaulters	Defaulters	Non-Defaulters
Fraction HHs w/ shock	23.2%	7.7%	42.1%	12.3%	66.8%	22.2%	13.2%	4.1%
# of HHs in Subgroup	190	5091	190	5091	190	5091	190	5091
	Recently Divorced?		Cash Flow Shock?		Any Non-Equity Shock?		High Hospital Bills?	
	Defaulters	Non-Defaulters	Defaulters	Non-Defaulters	Defaulters	Non-Defaulters	Defaulters	Non-Defaulters
Fraction HHs w/ shock	5.8%	2.0%	43.2%	16.4%	86.3%	56.3%	2.1%	1.0%
# of HHs in Subgroup	190	5091	190	5091	190	5091	190	5091

Notes: Default defined as 60+ days late as of survey date. PSID Sample includes heads of household who are mortgagors, ages 24-65, labor force participants with combined loan to value ratios less than 250% in 2009 and 2011. Cash flow shock includes recent divorce, unemployed head or spouse, or severe income loss of 50% or more. Any non-equity shock includes recent divorce, unemployment of head or spouse, a 50% reduction of income, low liquid assets, high hospital bills, or high medical bills. Subgroups of households defined in text, and all other shocks defined in text.

Table 4: Baseline Results: Linear Probability Model.

	Dependent Variable: 60+ Days Delinquent Indicator					
	(1)	(2)	(3)	(4)	(5)	(6)
LTV Ratio	0.096***	0.094***	0.087***	0.077***	0.099***	0.034
	(8.43)	(6.75)	(6.32)	(5.48)	(7.01)	(0.65)
Unemployed (d)	0.068***	0.053***	0.049***	-0.022		
	(4.75)	(3.73)	(3.55)	(-0.72)		
Spouse Unemployed (d)	0.036**	0.040**	0.034**	0.035**		
	(2.19)	(2.48)	(2.14)	(2.19)		
Low Liquid Assets (d)			0.054***	0.053***		
			(6.52)	(6.46)		
High Hospital Bills (d)			0.045	0.043		
			(1.41)	(1.35)		
High Medical Bills (d)			0.005	0.005		
			(0.91)	(0.85)		
Recently Divorced (d)			0.033	0.033		
			(1.20)	(1.20)		
High Unsecured Debt (d)			0.002	0.003		
			(0.18)	(0.22)		
LTV * Unemployed (d)				0.100**		
				(2.10)		
State UR					-0.001	-0.006
					(0.48)	(1.52)
LTV * State UR						0.007
						(1.20)
Demographic Controls	N	Y	Y	Y	Y	Y
Mortgage Controls	N	Y	Y	Y	Y	Y
State Controls	N	Y	Y	Y	Y	Y
# Households	5,281	5,281	5,281	5,281	5,281	5,281
R^2	0.043	0.082	0.097	0.100	0.073	0.073

Notes: Robust t-statistics in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Default defined as 60+ days late as of survey date. PSID Sample includes heads of household who are mortgagors, ages 24-65, labor force participants with combined loan to value ratios less than 250% in 2009 and 2011.

Table 5: Baseline Results: Logit Model.

Dependent Variable: 60+ Days Delinquent Indicator	(1)	(2)	(3)	(4)
LTV Ratio	0.068***	0.052***	0.053**	0.024***
	(9.63)	(10.83)	(7.59)	(6.66)
Unemployed (d)	0.063***	0.054***	0.026***	0.013***
	(4.57)	(4.32)	(4.00)	(4.18)
Spouse Unemployed (d)	0.026**	0.025***	0.021*	0.011***
	(1.99)	(2.96)	(1.91)	(2.84)
Low Liquid Assets (d)		0.039***		0.017***
		(6.91)		(6.46)
High Hospital Bills (d)		0.042**		0.018**
		(2.30)		(2.29)
High Medical Bills (d)		0.001		0.000
		(0.10)		(0.10)
Recently Divorced (d)		0.022**		0.010**
		(2.00)		(2.00)
High Unsecured Debt (d)		0.005		0.002
		(0.51)		(0.51)
LTV * Unemployed (d)		0.023		0.022
		(0.89)		(1.52))
Demographic Controls	N	Y	N	Y
Mortgage Controls	N	Y	N	Y
State Controls	N	Y	N	Y
# Households	5,268	5,268	5,268	5,268

Notes: Columns (1) and (2) report Average Marginal Effects (AMEs), while Columns (3) and (4) report Marginal Effects at the Mean (MEMs). Robust t-statistics are in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Default defined as 60+ days late as of survey date. PSID Sample includes heads of household who are mortgagors, ages 24-65, labor force participants with combined loan to value ratios less than 250% in 2009 and 2011.

Table 6: Robustness Checks, Linear Probability Model. Cols. (1) and (2) control for involuntary job loss. Cols. (3) and (4) control for prior unemployment spells. Cols. (5) and (6) control for forward house price growth. Cols. (7) and (8) control for lagged house price growth.

	Invol. Sep.		**Prior Unempl.**		**Forward HP**		**Lagged HP**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LTV	0.088***	0.086***	0.087***	0.076***	0.071***	0.067***	0.084***	0.071***
	(6.43)	(6.17)	(6.27)	(5.43)	(3.32)	(3.05)	(5.75)	(4.83)
Involuntarily Separated (d)	0.047**	0.005						
	(2.45)	(0.12)						
LTV *Involuntarily Separated (d)		0.060						
		(0.90)						
Involuntarily Separated Spouse (d)	0.055	0.056*						
	(1.64)	(1.69)						
Unemployed (d)			0.048***	-0.024	0.059***	0.029	0.058***	-0.038
			(3.48)	(-0.80)	(2.61)	(0.59)	(3.79)	(-1.12)
LTV * Unemployed (d)				0.101**		0.043		0.138**
				(2.13)		(0.55)		(2.47)
Spouse Unemployed (d)			0.034**	0.035**	0.050*	0.052*	0.036**	0.036**
			(2.11)	(2.16)	(1.81)	(1.89)	(2.03)	(2.04)
Low Liquid Assets (d)	0.056***	0.056***	0.054***	0.053***	0.040***	0.040***	0.049***	0.048***
	(6.66)	(6.64)	(6.50)	(6.44)	(3.09)	(3.09)	(5.44)	(5.38)
High Hospital Bills (d)	0.045	0.044	0.045	0.043	-0.021	-0.021	0.055	0.052
	(1.39)	(1.38)	(1.39)	(1.32)	(-1.39)	(-1.46)	(1.53)	(1.45)
High Medical Bills (d)	0.005	0.006	0.004	0.004	0.004	0.004	0.012*	0.011*
	(1.00)	(1.02)	(0.75)	(0.69)	(0.49)	(0.50)	(1.93)	(1.85)
Divorce (d)	0.034	0.033	0.034	0.034	0.007	0.006	0.056	0.055
	(1.21)	(1.20)	(1.21)	(1.21)	(0.23)	(0.21)	(1.21)	(1.19)
High Unsecured Debt (d)	0.003	0.004	0.003	0.004	0.015	0.015	-0.009	-0.009
	(0.27)	(0.32)	(0.25)	(0.30)	(0.69)	(0.69)	(-0.77)	(-0.74)
Lagged House Price Growth							0.002	0.002
							(0.36)	(0.44)
Forward House Price Growth					-0.000	0.000		
					(-0.00)	(0.02)		
1 Prior Unemployment Spell (d)			0.001	0.001				
			(0.11)	(0.11)				
2 Prior Unemployment Spells (d)			0.048*	0.049**				
			(1.95)	(2.00)				
3 Prior Unemployment Spells (d)			-0.046	-0.045				
			(-1.62)	(-1.56)				
4 Prior Unemployment Spells (d)			-0.009	-0.007				
			(-0.20)	(-0.16)				
5 Prior Unemployment Spells (d)			-0.077***	-0.079***				
			(-3.45)	(-3.69)				
7 Prior Unemployment Spells (d)			0.123	0.124				
			(0.58)	(0.58)				
Demographic Controls	Y	Y	Y	Y	Y	Y	Y	Y
Mortgage Controls	Y	Y	Y	Y	Y	Y	Y	Y
State Controls	Y	Y	Y	Y	Y	Y	Y	Y
Observations	5,281	5,281	5,281	5,281	2,151	2,151	4,310	4,310
R-squared	0.094	0.094	0.100	0.102	0.094	0.094	0.100	0.105

Notes: Robust t-statistics in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Default defined as 60+ days late as of survey date. PSID Sample includes heads of household who are mortgagors, ages 24-65, labor force participants with combined loan to value ratios less than 250% in 2009 and 2011. Involuntary job loss includes, plant closures, strike/lockout, and layoff. Forward and lagged house price growth defined as percentage change in self-reported home value. Dummies for prior unemployment include all types of unemployment spells from 1994-2005.

Table 7: Cols. (1) and (2) illustrate the impact of cash flow shocks (unemployment of head or spouse, divorce, or 50% income loss) on default, Cols. (3) and (4) illustrate the impact of any non-equity shock on default, and Cols. (5) and (6) illustrate the impact of a 50% income loss on default

	(1)	(2)	(3)	(4)	(5)	(6)
LTV	0.093***	0.073***	0.095***	0.049***	0.097***	0.095***
	(6.73)	(5.24)	(6.80)	(3.24)	(6.92)	(6.73)
Cash Flow Shock (d)	0.052***	-0.019				
	(5.52)	(-0.84)				
Cash Flow Shocks (d) * LTV		0.097***				
		(2.86)				
Any Non-Equity Shock (d)			0.026***	-0.023*		
			(5.79)	(-1.84)		
Any Non-Equity Shock (d) * LTV				0.070***		
				(3.41)		
Income Loss<50% (d)					0.069***	0.030
					(3.52)	(0.67)
Income Loss<50% (d) * LTV						0.057
						(0.84)
Demographic Controls	Y	Y	Y	Y	Y	Y
Mortgage Controls	Y	Y	Y	Y	Y	Y
State Controls	Y	Y	Y	Y	Y	Y
Observations	5,281	5,281	5,281	5,281	5,281	5,281
R-squared	0.085	0.089	0.078	0.081	0.079	0.080

Notes: Robust t-statistics in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Default defined as 60+ days late as of survey date. PSID Sample includes heads of household who are mortgagors, ages 24-65, labor force participants with combined loan to value ratios less than 250% in 2009 and 2011. Cash flow shock includes recent divorce, unemployed head or spouse, or severe income loss of 50% or more. Any non-equity shock includes recent divorce, unemployment of head or spouse, a 50% reduction of income, low liquid assets, high hospital bills, or high medical bills.

Table 8: Summary Statistics for 'Can Pay'/'Can't Pay' households.

	Can Pay				Can't Pay			
	All		Defaulters		All		Defaulters	
	Mean	p50	Mean	p50	Mean	p50	Mean	p50
(A) Demographics								
White (d)	0.81	1	0.35	0	0.55	1	0.49	0
Black (d)	0.14	0	0.53	1	0.34	0	0.32	0
Age	46.05	47	44.06	44	44.72	46	43.46	42
Male (d)	0.89	1	0.77	1	0.76	1	0.68	1
Married (d)	0.81	1	0.59	1	0.62	1	0.57	1
Less than High School (d)	0.04	0	0.00	0	0.18	0	0.14	0
High School Education (d)	0.20	0	0.18	0	0.37	0	0.43	0
Some College Education (d)	0.24	0	0.47	0	0.19	0	0.16	0
College Grad+ Education (d)	0.52	1	0.35	0	0.23	0	0.27	0
Number of Children	0.90	0	1.18	1	1.03	1	1.00	0
Income	140,000	110,000	91,000	68,000	64,000	58,000	44,000	37,000
(B) Mortgage Characteristics								
	Can Pay				**Can't Pay**			
	All		Defaulters		All		Defaulters	
	Mean	p50	Mean	p50	Mean	p50	Mean	p50
Home value	310,000	240,000	260,000	200,000	160,000	130,000	200,000	130,000
Principal Remaining	160,000	130,000	280,000	240,000	110,000	90,000	160,000	110,000
Monthly Mortgage Payment	1,375	1,200	1,907	1,850	966	800	1,258	1,100
Second Mortgage (d)	0.18	0	0.35	0	0.17	0	0.22	0
Refinanced Mortgage (d)	0.53	1	0.41	0	0.37	0	0.32	0
ARM (d)	0.07	0	0.24	0	0.12	0	0.24	0
Mortgage Interest Rate	4.89	5	4.53	6	5.68	6	5.03	5
Mortgage Term Remaining	19.06	20	25.18	25	20.44	23	22.92	24
Recourse (d)	0.25	0	0.24	0	0.22	0	0.22	0
Judicial (d)	0.40	0	0.47	0	0.42	0	0.54	1
Default (60+ Days Late) (d)	0.01	0	1.00	1	0.19	0	1.00	1
Months Delinquent	0.04	0	4.65	3	1.13	0	5.57	4
Loan to Value Ratio	0.62	0.612	1.25	1.019	0.80	0.787	0.93	0.878
(C) **Employment**								
	Can Pay				**Can't Pay**			
	All		Defaulters		All		Defaulters	
	Mean	p50	Mean	p50	Mean	p50	Mean	p50
Unemployed Head Last Year (d)	0.02	0	0.00	0	1.00	1	1.00	1
Unemployed Spouse Last Year (d)	0.04	0	0.12	0	0.12	0	0.22	0
Unemployed Head or Spouse Last Year (d)	0.06	0	0.12	0	1.00	1	1.00	1
Head Unemployed as of Survey Date (d)	0.00	0	0.00	0	1.00	1	1.00	1
Spouse Unemployed as of Survey Date (d)	0.03	0	0.00	0	0.12	0	0.22	0
(D) Wealth								
	Can Pay				**Can't Pay**			
	All		Defaulters		All		Defaulters	
	Mean	p50	Mean	p50	Mean	p50	Mean	p50
Value of Stocks	51,000	0	29000	0	212	0	108.11	0
Value of Liquid Assets	42,000	20,000	21,000	4,000	2,615	500	648	0
Unsecured Debt	6,720	400	25,000	16,000	28,000	9,953	29,000	5,000
Value of Vehicles	24,000	18,000	17,000	20,000	11,000	7,250	8,156	8,000
Value of Bonds	33,000	0	160,000	25,000	482	0	270	0
Value of Business	81,000	0	1,875	0	11,000	0	56	0
Value of IRA	59,000	0	15,000	0	14,000	0	0	0
N		2126		17		193		37

Notes: PSID Sample includes heads of household who are mortgagors, ages 24-65, labor force participants with combined loan to value ratios less than 250% in 2009 and 2011. Can Pay: Head employed with at least 6 mo. worth of mortgage payments in stocks, bonds, or liquid assets net of unsecured debt. Can't pay: Head is unemployed and has less than 1 month's worth of mortgage payments in stocks, bonds, or liquid assets net of unsecured debt. Won't Pay: Can pay borrowers who default. Don't Pay: Can't pay borrowers who default.

Table 9: Alternate Definitions of "Can Pay" and "Can't Pay"

	Can Pay	**Can't Pay**
Default Rate, Baseline Definition	0.008	0.192
N	2126	193
Default Rate, Baseline Definition w/ Negative Equity (CLTV$\geq$1)	0.052	0.333
N	174	39
Default Rate, Baseline Definition w/ CLTV$\geq$.9	0.038	0.281
N	341	64
Default Rate, Alternate Definition	0.016	0.266
N	2884	94
Default Rate, Alternate Definition w/ Negative Equity (CLTV$\geq$1)	0.061	0.304
N	344	23
Default Rate, Alternate Definition w/ CLTV$\geq$.9	0.037	0.242
N	720	33

Notes: PSID Sample includes heads of household who are mortgagors, ages 24-65, labor force participants with combined loan to value ratios less than 250% in 2009 and 2011. Baseline Definition of "Can Pay": Head employed with at least 6 mo. worth of mortgage payments in stocks, bonds, or liquid assets net of unsecured debt. Baseline Definition of "Can't Pay": Head is unemployed and has less than 1 month's worth of mortgage payments in stocks, bonds, or liquid assets net of unsecured debt. "Baseline Definition w/ Negative Equity" imposes additional restriction that Combined Loan to Value (CLTV) is greater than or equal to 1. Alternate Definition of "Can Pay": includes all households who have had no unemployment spells and have one of either (i) at least 6 months worth of mortgage payments in stocks, bonds, or liquid assets net of unsecured debt or (ii) a DTI$<$ 31%. Alternate Definition of "Can't Pay": households have both (i) an unemployed head and a non-employed spouse and (ii) has less than 1 month's worth of mortgage payments in stocks, bonds, or liquid assets net of unsecured debt. "Alternate Definition w/ Negative Equity" imposes additional restriction that Combined Loan to Value (CLTV) is greater than or equal to 1.

Table 10: Sensitivity of Can't Pay and Can Pay Households to Equity

	(1)	(2)	(3)	(4)
	Can't Pay	Can't Pay	Can Pay	Can Pay
LTV	0.123*	0.100	0.049***	0.049***
	(1.86)	(1.43)	(3.13)	(3.19)
Demographic Controls	Y	Y	Y	Y
State Controls	N	Y	N	Y
Observations	193	193	2,126	2,126
R-squared	0.122	0.162	0.063	0.069

Notes: Robust t-statistics in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$. PSID Sample includes heads of household who are mortgagors, ages 24-65, labor force participants with combined loan to value ratios less than 250% in 2009 and 2011. Can Pay: Head employed with at least 6 mo. worth of mortgage payments in stocks, bonds, or liquid assets net of unsecured debt. Can't pay: Head is unemployed and has less than 1 month's worth of mortgage payments in stocks, bonds, or liquid assets net of unsecured debt.

Table 11: Wealth Distribution of Defaulters with Negative Equity.

Panel A: Defaulters with LTV>1, 2009-2011

	Mean	p10	p25	p50	p75	p90	sd	N
Liquid Assets to Mortgage Payment Ratio	1.24	0.00	0.00	0.28	1.26	3.33	2.81	78
Illiquid Assets to Mortgage Payment Ratio	15.72	0.00	2.50	6.44	16.15	31.29	34.03	80
Liquid+Illiquid Assets- Unsecured Debt to Mortgage Payment Ratio	7.48	-12.96	-2.27	2.99	10.57	22.87	39.04	78
Liquid + Stocks and Bonds to Mortgage Payment Ratio	7.87	0.00	0.00	0.44	1.76	4.55	34.15	78

Panel B: Defaulters with LTV>1, Weighted, 2009-2011

	Mean	p10	p25	p50	p75	p90	sd	N
Liquid Assets to Mortgage Payment Ratio	1.46	0.00	0.00	0.64	1.82	4.02	3.06	78
Illiquid Assets to Mortgage Payment Ratio	14.14	0.00	1.34	4.80	15.63	30.06	30.45	80
Liquid+Illiquid Assets- Unsecured Debt to Mortgage Payment Ratio	6.37	-11.81	-2.04	2.50	10.75	20.86	34.01	78
Liquid + Stocks and Bonds to Mortgage Payment Ratio	6.45	0.00	0.01	0.68	1.84	4.05	29.34	78

Panel C: All Defaulters, 2009-2011

	Mean	p10	p25	p50	p75	p90	sd	N
Liquid Assets to Mortgage Payment Ratio	2.21	0.00	0.00	0.22	1.28	3.81	13.56	186
Illiquid Assets to Mortgage Payment Ratio	23.62	0.00	2.94	7.70	18.18	38.16	56.68	190
Liquid+Illiquid Assets- Unsecured Debt to Mortgage Payment Ratio	12.40	-27.06	-3.86	3.57	13.51	36.44	62.16	186
Liquid + Stocks and Bonds to Mortgage Payment Ratio	9.23	0.00	0.00	0.29	1.76	5.00	38.88	186

Panel D: All Defaulters, Weighted, 2009-2011

	Mean	p10	p25	p50	p75	p90	sd	N
Liquid Assets to Mortgage Payment Ratio	4.00	0.00	0.00	0.37	1.62	4.00	21.78	186
Illiquid Assets to Mortgage Payment Ratio	25.38	0.00	2.50	6.37	17.23	35.79	64.72	190
Liquid+Illiquid Assets- Unsecured Debt to Mortgage Payment Ratio	17.74	-19.87	-3.13	3.67	12.92	46.32	71.00	186
Liquid + Stocks and Bonds to Mortgage Payment Ratio	11.11	0.00	0.01	0.47	1.98	4.55	40.62	186

Notes: PSID Sample includes heads of household who are mortgagors, ages 24-65, labor force participants with combined loan to value ratios less than 250% in 2009 and 2011. Liquid assets include checking and savings account balances, money market funds, certificates of deposit, Treasury securities, and other government saving bonds. Illiquid assets include stocks, bonds, vehicles, business income, and retirement income. Assets are expressed as a ratio of the monthly mortgage payment.

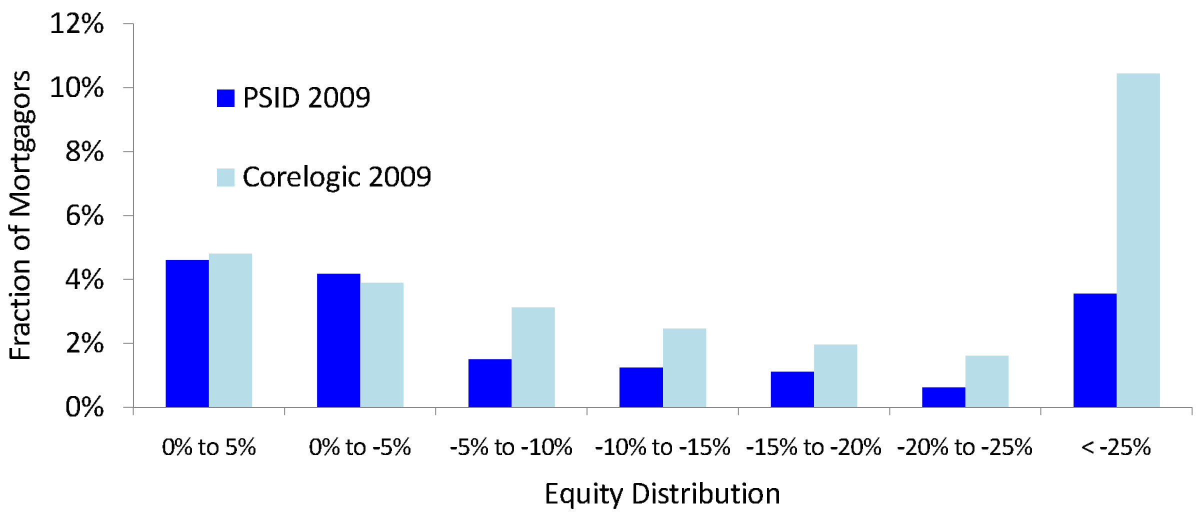
Table 12: Wealth Distribution of Non-Defaulters.

	Non-Defaulters, 2009-2011							
	Mean	**p10**	**p25**	**p50**	**p75**	**p90**	**sd**	**N**
Liquid Assets to Mortgage Payment Ratio	21.58	0.00	1.20	4.55	13.89	37.41	290.62	4919
Illiquid Assets to Mortgage Payment Ratio	296.54	2.47	7.94	21.27	66.12	220.00	9963.94	5090
Liquid+Illiquid Assets- Unsecured Debt to Mortgage Payment Ratio	185.65	-14.75	3.06	22.39	78.45	253.03	5341.97	4919
Liquid + Stocks and Bonds to Mortgage Payment Ratio	46.77	0.00	1.56	6.72	25.64	90.63	324.39	4919

	Non-Defaulters, Weighted, 2009-2011							
	Mean	**p10**	**p25**	**p50**	**p75**	**p90**	**sd**	**N**
Liquid Assets to Mortgage Payment Ratio	22.45	0.00	1.54	5.52	16.67	43.10	211.92	4919
Illiquid Assets to Mortgage Payment Ratio	272.62	2.75	8.51	24.38	87.50	283.33	8414.80	5090
Liquid+Illiquid Assets- Unsecured Debt to Mortgage Payment Ratio	222.48	-11.53	5.00	27.80	105.88	320.63	5910.51	4919
Liquid + Stocks and Bonds to Mortgage Payment Ratio	55.51	0.14	2.12	8.54	33.33	119.05	277.71	4919

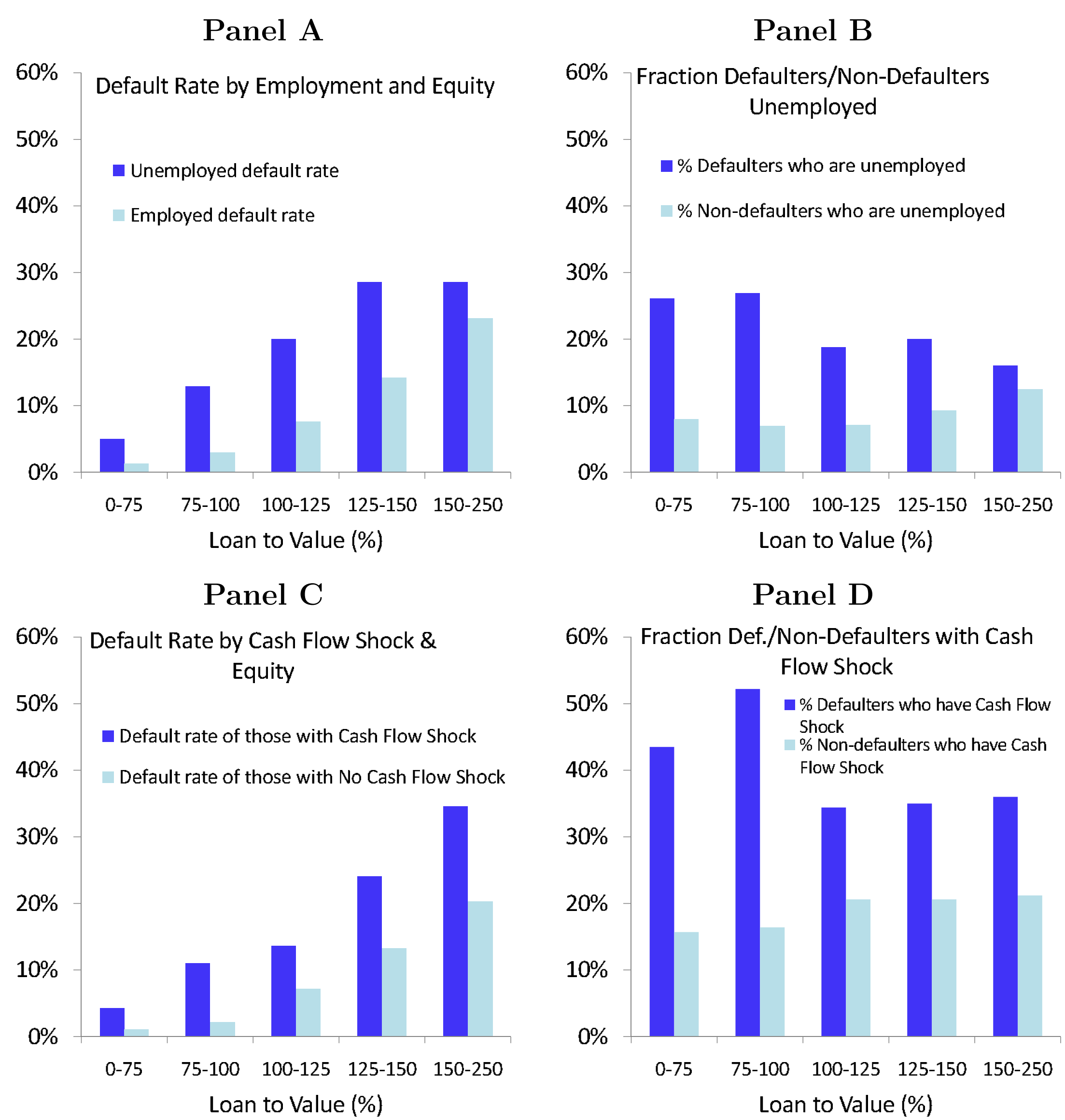
Notes: PSID Sample includes heads of household who are mortgagors, ages 24-65, labor force participants with combined loan to value ratios less than 250% in 2009 and 2011. Liquid assets include checking and savings account balances, money market funds, certificates of deposit, Treasury securities, and other government saving bonds. Illiquid assets include stocks, bonds, vehicles, business income, and retirement income. Assets are expressed as a ratio of the monthly mortgage payment.

Figure 1. Equity Distribution.



Notes: PSID Sample includes heads of household who are mortgagors, ages 24-65, labor force participants with combined loan to value ratios less than 250% in 2009 and 2011. CoreLogic data taken as of 2009, "First American CoreLogic Releases Q3 Negative Equity Data," available from `http://www.recharts.com/reports/FACLNERQ32009/FACLNERQ32009.pdf`

Figure 2. Default Rate by Shocks and Equity. Fraction of Defaulters/Non-Defaulters with Shocks by Equity.



Notes: Default defined as 60+ days late as of survey date. PSID Sample includes heads of household who are mortgagors, ages 24-65, labor force participants with combined loan to value ratios less than 250% in 2009 and 2011. Cash flow shock includes recent divorce, unemployed head or spouse, or severe income loss of 50% or more. Unemployed includes both those unemployed last year and as of the survey date.

Figure 3. Definition of Types of Defaults.

	Did Pay	Didn't Pay
Can Pay	**(1)** **Repayment**	**(2)** **Type I Error** **"Won't Pay"** **Strategic Default**
Can't Pay	**(3)** **Type II Error** **"Will Pay"**	**(4)** **"Normal"** **Non-Strategic Default**